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Toward efficient quality of information estimation in simultaneous acoustic tracking and classification of multiple targets

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Abstract – *An individual sensor's information output is often insufficient for an application, with ambiguities that require refinement or corroboration by fusion with information from other sensors. Fusion of multiple information sources is performed to create an information product of higher quality of information (QoI) that supports more effective intelligence, surveillance, and reconnaissance (ISR). In this paper we present an approach to determining the QoI attributes (metadata) relevant to tracking and classification of multiple vehicles, and the necessary weighting (qualifying) terms, as information derived from multiple acoustic sensors is fused. Field trial data is used to validate the conclusions.*

Keywords: Quality of information (QoI), sensor fusion, intelligence, surveillance and reconnaissance (ISR/ISTAR), tracking, classifier.

1 Introduction

Information quality has been studied extensively in the context of data collected and stored in data warehouses [14, 15], and it covers issues such as accuracy, timeliness, completeness, consistency, etc. On the other hand, *quality of information* (QoI) for sensor networks has attracted significantly less attention; however, there is an increased interest in the area lately [16, 17]. QoI pertains to the capability of assessing how well information available to an end-user (an analyst, a decision maker, or a computer process) can be used to reconstruct portions of the real world that are of interest. As stated metaphorically in [18], QoI can broadly be viewed as the ability of a painter to paint, using the information collected, desired aspects of the real world accurately and timely enough for viewers of the painting to perform their tasks that relate to the painted world at desired levels of effectiveness.

A decision-maker generally requires a well-founded method for ascribing confidence and importance to intelligence provided by a wide spectrum of sources. In this paper we consider sensor intelligence (SENSINT) provided by a trusted sensor network as accurately timed streams of location and classification information pertaining to *multiple targets*. The confidence estimates we require must come from some combination of prior analysis of the response of the sensing service, projections of the potential target types and behaviors (assuming a quiet environment in this case), and the measurements from the sensors, themselves. The novel analysis provides a method for generating a simple, effective summary of the QoI emitted by the sensor network. This comes from using the relationship between the *quality of the data* (QoD) and the resultant QoI to guide the derivation of simple QoI *qualifiers* that dictate which information sources should be used in a simple but effective tactical framework. The experimental results comprise tracking and classification of multiple vehicles moving in inhomogeneous groups. We discuss the potential benefits of derived QoI summaries for a decision-making task, and outline some of the further work in which we intend to explore them.

2 Background

To generate comprehensive situational awareness in a location of interest, several sensors of multiple modalities are deployed. Each sensor provides partial information about the situation; often imperfections such as bias, envelope limits, and susceptibility to environmental or tactical compromise impact the fundamental validity of that information. Such imperfect information must be fused in a suitable manner to achieve reasonable understanding of the situation. Fusion is intended both to complete constraint in the measurement task, and to improve the quality of information (QoI), with the goal of increasing its value (the value of information, or VoI) to the application or other recipients [1-3]. The modeling performed as part of synthesizing a fusion process (*e.g.* location+Gaussian noise motivates weighted averaging) may be rendered irrelevant if the source behaviours do not comply with the modeling assumptions. If fusion is performed without understanding the limitations of the sensors involved, the QoI may, in fact, deteriorate. QoI provides a framework for reasoning about sensor network performance and enables deployment of sensors for optimal utility [3].

The precise methods for use of QoI estimates are application specific [3]. Often, the user has a notion of what is acceptable (better QoI) and what is unacceptable (poorer

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14. ABSTRACT
An individual sensor?s information output is often insufficient for an application, with ambiguities that require refinement or corroboration by fusion with information from other sensors. Fusion of multiple information sources is performed to create an information product of higher quality of information (QoI) that supports more effective intelligence, surveillance, and reconnaissance (ISR). In this paper we present an approach to determining the QoI attributes (metadata) relevant to tracking and classification of multiple vehicles and the necessary weighting (qualifying) terms, as information derived from multiple acoustic sensors is fused. Field trial data is used to validate the conclusions.

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QoI). Intuitively, fusion of information is guided by this notion of good and bad, applying varying weight to each item of information in the derivation of the appropriate conclusion. When it comes to calculation, the semantics of the problem and available assets enable us to specify a suitable class of fusion functions for using the available QoI *attributes* (in operation, these are provided as *metadata* accompanying the information [3]), and the particular circumstances give the qualifiers necessary to achieving the best result in terms of QoI for the particular instantiation.

The meaning of an information product is generally a probabilistic constraint on the potential states of the aspects of ground truth instrumented by the combined intelligence sources. For example, a tracking information product will state that the locations of the target that could have given rise to the tracker's estimate are distributed in some manner, for example as a mean and a variance.

Selection of sensor modalities also depends on the notion of good QoI desired for intelligence, surveillance, and reconnaissance (ISR) [3]. As a result, video (imaging) sensors are the dominant sensors deployed for gathering ISR, because the information quality is regarded as obvious to the user. We are looking for an effective, pragmatic approach to fusion with the QoI in a sensor network by fusing only the sensor outputs, which we can quickly assess as resulting in high QoI. This selection process includes an example of QoI *qualifiers* that provide guidance on how information and associated QoI should be fused.

In this paper we explore the QoI in a multiple target tracking scenario. We formulate simple but effective guidelines for fusing direction of arrival (DOA) angle information of a target from different sensors to estimate the location of the target. In the signal processing literature, several bounds are given for achievable location accuracy. For example, the Cramer-Rao bound (CRB) [4, 5] identifies the overall accuracy that *can* be obtained for a set of sensors with *identical* noise statistics. We do not have a simple, computationally frugal way of determining the true achievable accuracy if the noise statistics change during the course of sensor usage. If we can formulate a fusion policy that guarantees the true information quality is sufficiently close to the CRB, then the CRB is a candidate QoI approximator [5]. Intuitively, the best quality may be achieved if the sensors with minimal noise characteristics are used. A policy based on this intuition dictates the usage of sensors with high signal to noise ratio at any given time.

In the case of vehicle tracking using a Kalman filter, we do not have a simple CRB. When we address a joint purpose of tracking and classification, the accuracy components of QoI are estimated probability distributions of location and vehicle type.

Rather than presenting a decision-maker with panoply of information quality indicators, he/she may be better served with one overall QoI indicator for each target, tailored to his/her specific decision task. This will require an *ante hoc* analysis of the range of situations within which decisions are to be made. This means that the information quality indicator is conditional on some description of the circumstances. Intuitively, the more detailed this description, the more effective we would expect a quality indicator to be. We will analyze this presumption in a follow-on paper. For now, we simply demonstrate that it is possible to summarize the information quality from a sensing service to give an indicator function that trends positively with a correct decision.

This paper suggests an estimate of a suitable overall QoI value from individual QoI values generated by the various intelligence sources—in our case the angle estimator, tracker, classifier, etc. To aid in the derivation and exploitation of fusion for QoI, we use the following problem statement:

Problem statement: Identify any heavy tracked vehicle approaching the northbound gate and intercept it. The sensor suites available to track and identify the vehicles are acoustic sensors.

In section 3 we present the architecture for the tracking and classification of multiple targets using sensor fusion for QoI. In section 4 we present the QoI-based fusion to achieve better quality of tracking and classification of multiple vehicles using acoustic sensor arrays. We also discuss issues involved in achieving better QoI. In section 5 we present the discussions and further work. Section 6 presents conclusions.

3 Framework for simple QoI guided sensor fusion

There are six acoustic sensor arrays deployed in the middle of the track, as shown in figure 1. Each acoustic sensor array consists of seven microphones with six of the microphones placed on the vertices of a regular hexagon (circular array), and the seventh microphone placed at the center of the array. Each array is capable of determining the direction of arrival (DOA) of an acoustic signal that may be emanating from a vehicle using hyper-spectral techniques, such as minimum variance distortionless response (MVDR) or multiple signal classification (MUSIC) algorithms [6]. The target set consists of one heavy tracked vehicle, one light tracked vehicle, one heavy wheeled truck, and one light wheeled truck. Initially, all the vehicles are stationed on the north end of the track and idling. A test-run consists of the heavy tracked vehicle followed by the heavy wheeled truck, the light wheeled truck, and then the light tracked vehicle, traveling at 16 to 32 Km/h with a separation of 100-200m between them. Acoustic signals from the vehicles are analyzed to determine the DOAs and their classification at

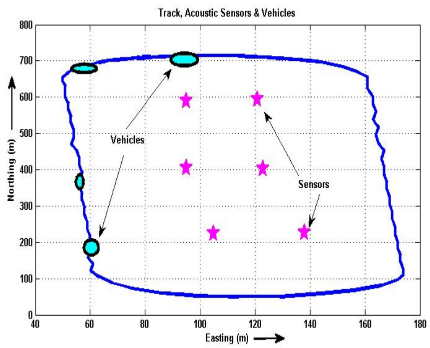

Figure 1. Tracking scenario with acoustic sensors

each sensor array. Figure 2 shows the overall scheme for processing the information to determine the individual tracks and classification of the vehicles.

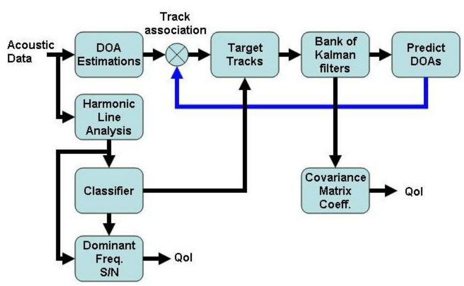

Figure 2: Architecture for Tracking and Classification of multiple vehicles

There are three major modules in the architecture for the vehicle tracking application, namely, (a) Estimation of target coordinates (Target tracks) using DOAs of targets from different sensor arrays, (b) Kalman filtering, and (c) classifier. In figure 2, the "DOA Estimation" module generates six (number of mics in the array minus one) DOA angles per sensor array. The DOA angle corresponding to the strongest signal is listed first, followed by the others according to their signal strengths. Notice that there are only

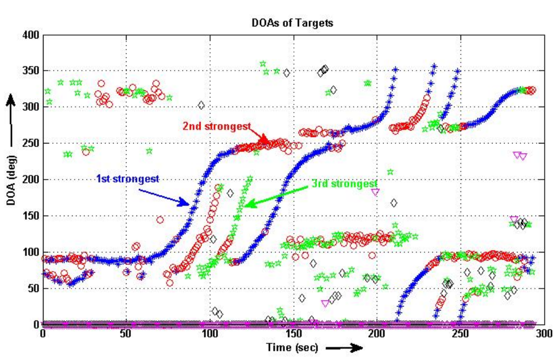

Figure 3: Output of a sensor array showing four angle tracks corresponding to four vehicles

four vehicles; despite this, each sensor array generates six DOA angles, two of which are artifacts. It is possible that some of the artifacts are due to the signals reflected by a nearby building or an unknown acoustic signal source in the vicinity. A typical output of DOAs generated by a sensor array is shown in figure 3. One can clearly see four different angle tracks. As the target comes close to the closest point of approach (CPA) of a sensor array, the target's signal becomes the strongest and its DOA will be listed first irrespective of its order among the vehicles, which can be seen clearly in figure 3. Each sensor array outputs its metadata information as follows:

Time	**Sensor coords**	**DOA1**	**CLS1**	**SNR1**	**DOA2**	**…**

Table 1: Metadata from a sensor array

The metadata consists of time-stamp, sensor coordinates, DOA1 corresponding to the strongest signal, its classification, and its SNR, followed by the DOA2 corresponding to the 2nd strongest signal, its classification, its SNR, etc. The DOAs from the sensor arrays are used to generate the target coordinates and tracks in the module "Target Tracks" in figure 2. Initially, there will be several false tracks that will die out shortly after the targets move. Bank of Kalman filters [6] are used to track the target tracks. The predicted coordinates of each target are used to generate the expected DOAs of each target, which are used for track association, as shown in figure 2. Note that track association will not happen until tracks are formed clearly. Classifier output is also used to assist the target tracks.

4 QoI based fusion of DOAs to estimate target location

If there are only two sensor arrays, then the only option is to use both the DOAs from both the sensor arrays to estimate the position [7, 8] of the target. However, if multiple arrays are present, then there are several ways one can determine the target location. Figure 4 shows the geometry for localization using DOAs. To make the presentation suitably

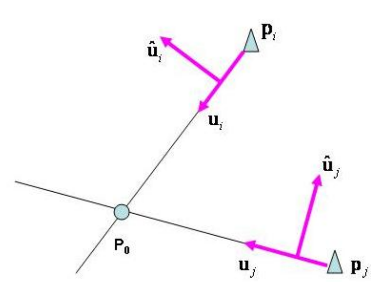

Figure 4: Geometry for Localization

self-contained, localization formulation [8] is presented here. Let P_i represent the location of i^{th} sensor array, while U_i and $\hat{U}_i$ represent the unit vectors in the direction of DOA

and its normal, respectively, and P_0 is the location of the target. Then from the geometry [9],

$$\begin{bmatrix} \hat{U}_1 \\ \hat{U}_2 \\ \vdots \\ \hat{U}_n \end{bmatrix} P_0 = \begin{bmatrix} \hat{U}_1 P_1 \\ \hat{U}_2 P_2 \\ \vdots \\ \hat{U}_n P_n \end{bmatrix} \qquad (1)$$

a linear equation (1) can be solved for target position P_0 using least squares methods. If the signal to noise ratio (SNR) at all sensor arrays is more or less the same, then use of all DOAs from all the sensors in (1) would result in best estimate of the target location. CRB gives the error limit on the localization based on the SNR [4, 5]. This bound could be used to measure the quality of location estimation (indicator of QoI) on the localization. If the SNR at some of the sensor arrays is widely different, then use of all DOAs in (1) would result in poor estimation of target location. To estimate the SNR at each sensor array, let us consider the propagation loss in acoustic signal '*S*' that is inversely proportionate to the square of distance

$$S = A/d^2 \qquad (2)$$

where '*A*' is the signal strength at the source and '*d*' denotes the distance between the source and the sensor. For the track shown in figure 5, the ratio between the closest and the farthest distance for a sensor array is approximately 15, which results in a difference of 23 db in SNR between the sensor array that is closest to the target and the sensor array that is farthest. This results in DOA accuracy from 2º to 10º. Realistic estimation of the CRB and, hence, the quality of target location estimation, is not possible. So, blind use of equation (1) does not provide a meaningful estimate of target location (that is, good QoI), as seen in figure 5.

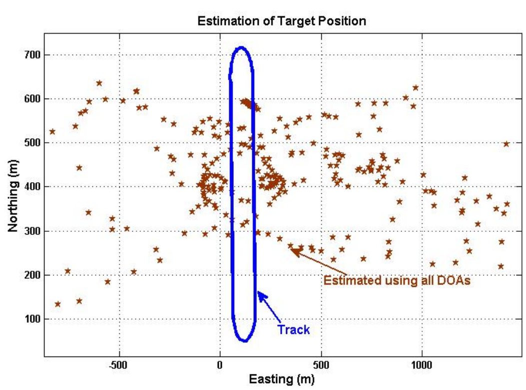

Figure 5: All DOAs fused to generate Target Location

Notice that when the sensor arrays and the targets are almost in line, even small errors in DOAs result in large errors. When the target is close to the mid-range, all sensor arrays provide a reasonable estimate of DOAs, resulting in estimates that are close to the track—since the arrays farther from the target have more error than the ones close to the target, the error in estimation of the target location changes from large to small, resulting in loops like the one in figure 5. In figure 6, the target locations are estimated using only the DOAs, which are close to the predicted DOAs of the expected target location. This process of selected fusion of DOAs resulted in better QoI.

Measure of QoI for Target Location Estimation: At each stage in figure 2, one can assign a value to the quality. The quality of coordinate estimation depends only on the DOA estimation. If these DOAs deviate from the actual values, the estimated target coordinates will be in significant error, resulting in poor quality. Hence, we propose the QoI to be inversely proportional to the difference between the estimated DOA, θ_e^i, and the actual DOAs, θ_a^i, for each sensor array '*i*' and it is given.

$$Q_t = \sum_{i=1}^{n} \frac{1}{\left\| \theta_e^i - \theta_a^i \right\|} \qquad (3)$$

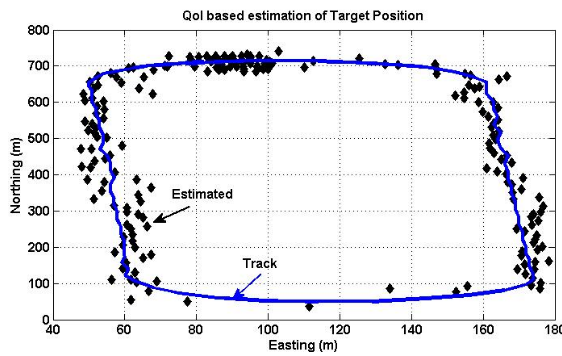

Figure 6: Selective DOA fusion for Target Location

The proposed measure for QoI gives us high confidence if it has large value, that is, the estimated values are close to the actual values. In reality the actual values may not be available or predicted apriori. In such a case, one can use the difference between the measured values and the predicted values using the predicted coordinates by the Kalman filter.

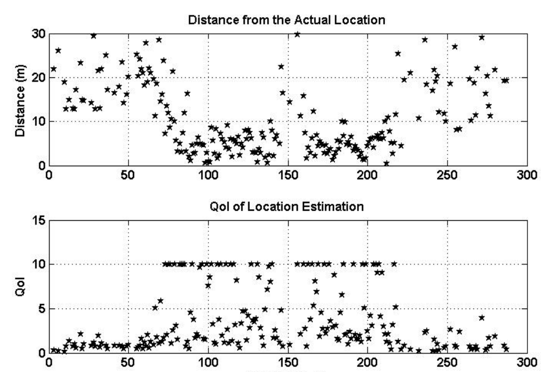

Figure 7: (a) Estimation accuracy (b) QoI measure

In figure 7, we presented the distance between the actual target location and the estimated position. Figure 7 also shows the quality of the target estimation by (3) with the upper limit set at 10. Clearly, from figure 7, we note that the target coordinates are close to the ground truth when QoI is high.

4.1 Tracking by Kalman Filters

The estimated target positions are fed to multiple Kalman filters [6] for tracking purposes. Kalman filters estimate the dynamic model of each target and update the track coordinates using both the model and the input. One of the parameters it estimates is the dynamic model of the track, which includes the covariance of the data. If the diagonal coefficients of the covariance matrix vary by a large number, it implies that the track coordinates are changing widely, indicating that the quality of information (quality of tracking) is not very good. If the coefficient is small, the track is following the model closely and the QoI is good. Figure 8 shows the output of the Kalman filters for targets 1 to 4.

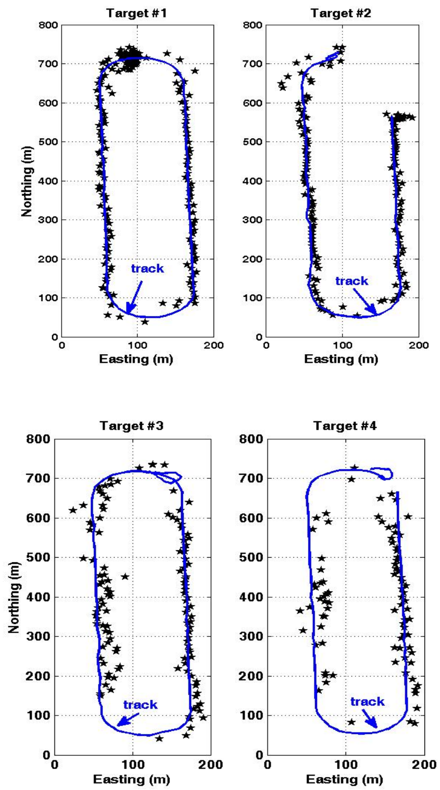

Figure 8: Outputs of Kalman filters for all four targets

Measure of QoI for Kalman Filtered Output: Since the coefficients provide us a measure on the variation of the coordinates, we propose the QoI of Kalman filtered output as

$$Q_k = \frac{1}{\sqrt{\left(C_{1,1}^2 + C_{2,2}^2\right)}} \tag{4}$$

where $C_{i,i}$ is the (i, i) coefficient of the covariance matrix for the Kalman filter tracking a particular target. Figure 9 shows how the QoI defined by (4) relates to the accuracy of tracking.

4.2 Vehicle Classification and its QoI

In order to aid track association, a multivariate Gaussian (MVG) classifier [9-12] is developed for vehicles. The acoustic signal of a ground vehicle, $s(t)$, can be modeled at any time, t, by a coupled harmonic signal model as

$$s(t) = \sum_{k=1}^{N} A_k \cos(2\pi k\ f_0 t + \phi_k) + n(t) \tag{5}$$

where k is the harmonic number, A_k is the amplitude of the k^{th} harmonic, f_0 is the fundamental frequency, ϕ_k is the phase of the k^{th} harmonic, N is the total number of harmonics, and $n(t)$ is the additive white Gaussian noise. The fundamental frequency is usually related to the RPM of the motor and determined by the *cylinder-firing rate*. The number of (detectable) harmonics, *N*, is a function of the vehicle type, detection range, and the classification algorithm used [11-13]. Figure 10 shows the spectrogram of target #1. The harmonics are clearly visible in figure 10. Notice also that the frequency changes as the Doppler changes.

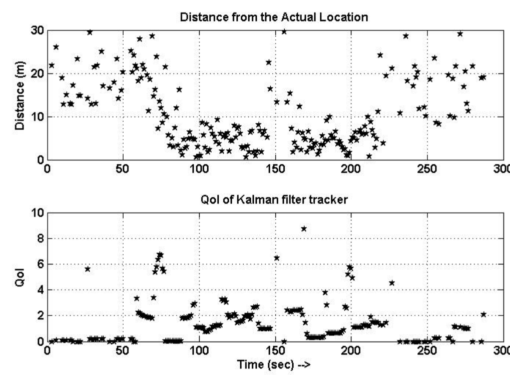

Figure 9: Coefficients of Covariance Matrix

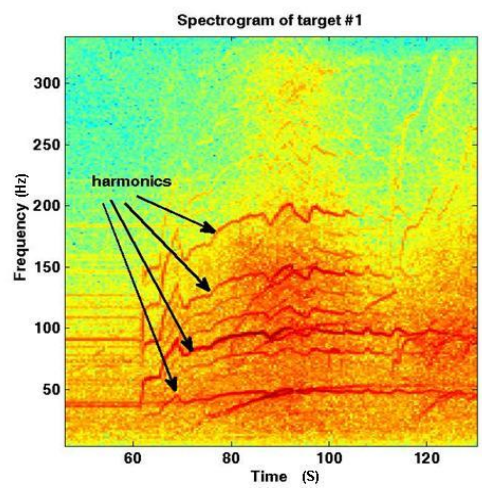

Figure 10: Spectrogram of target #1 signals

- **MVG Classifier**

Let us assume that we need to classify a pattern $X = (x_{1,} x_{2,} \cdots, x_N)$ into one of the R categories, and each

pattern is governed by one of the R distinct probability density functions $p(X|j),\ j=1,\cdots,R$, where $p(X|j)$ is the probability of occurrence of pattern X, given it belongs to category j. Now, in our case, $X=[x_1, x_2, \cdots, x_N]^T$ is a vector of N harmonic magnitudes, where T denotes the transpose. Assuming they obey the normal distribution, then the multivariate normal probability distribution of the pattern X is given by

$$p(X)=\frac{1}{(2\pi)^{N/2}|\Sigma|^{1/2}}\exp\left\{-\tfrac{1}{2}(X-M)^T\Sigma^{-1}(X-M)\right\} \quad (6)$$

where the mean, M and the covariance matrix Σ are defined as $M=E\{X\}=[m_1.m_2,\cdots,m_N]^T$

$$\Sigma=E\{(X-M)(X-M)^T\}=\begin{bmatrix}\sigma_{1,1} & \cdots & \sigma_{1,N}\\ \cdots & \ddots & \cdots\\ \sigma_{N,1} & \cdots & \sigma_{N,N}\end{bmatrix}, \quad (7)$$

and $\sigma_{pq}=E\left[(x_p-m_p)(x_q-m_q)\right], p,q=1,2,\cdots,N.$ It is assumed that the a priori probability $p(j)$ and the N–variate normal probability function $p(X|j)$ are known for each j. That is, we know R normal density functions. Let us denote the mean vectors M_i and the covariance matrices Σ_j for $j=1,\cdots,R,$ then we can write

$$p(X|H_j)=\frac{1}{(2\pi)^{N/2}|\Sigma_j|^{1/2}}\exp\left\{-\frac{(X-M_j)^T\Sigma_j^{-1}(X-M_j)}{2}\right\} \quad (8)$$

for all $j\in\{1,2,\cdots,R\}$ where $M_j=(m_{j1},m_{j2},\cdots,m_{jN})$. We used the Matlab function "*classify*" to classify the targets, and the classification results of signals from the direction of target #1 are shown in figure 11. While the classifier is unable to classify the target correctly most of the time, hence it is not good enough for track association. The reasons for misclassification could be: (a) varying speeds of the vehicle different from the training data set, (b) shift in gears can cause abrupt changes in the engine RPM, and (c) change in the road conditions compared to the training data. The problem is further complicated by the presence of other vehicles. We find tracking a dominant frequency from each vehicle and its SNR provides a better QoI on the vehicle classification.

Fusion for QoI: In order to isolate the signals from individual targets, we perform spatially filtering of the signals based on the bearing estimates of each target. We extract and record the dominant harmonic and its amplitude for each target. We track this dominant harmonic frequency for each target and classify the target based on this single dominant harmonic. As the target leaves one sensor array

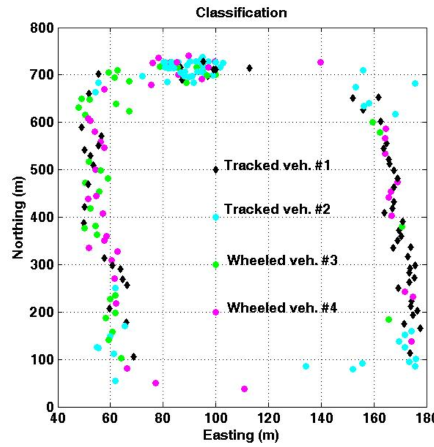

Figure 11: Classification of signals from target #1 direction

and approaches another, the harmonic frequency is tracked on the sensor array that is closest to the target. The fusion of the data from different arrays is the key for prolonged tracking and accurate classification.

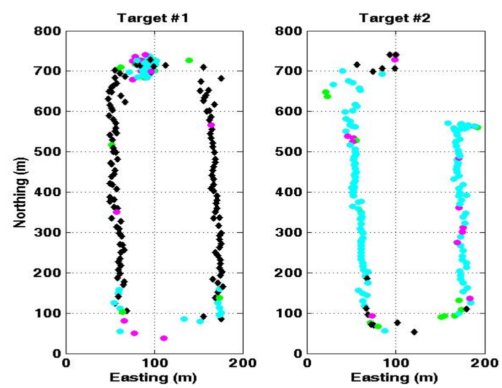

Figure 12: Classification of signals from direction of targets 1 & 2 using dominant frequency tracking

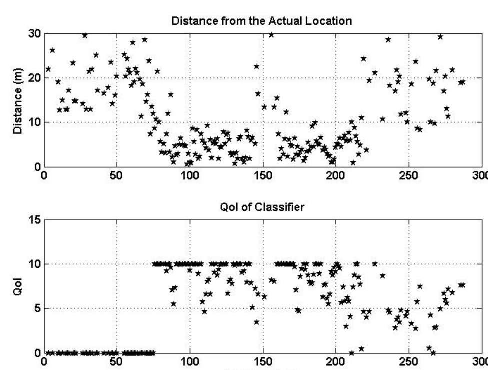

Figure 13: QoI of classifier

The resulting classifications of two targets are given in figure 12. As in figure 11, the different target classifications are depicted using different colors: black for target #1, cyan for target #2, green for target #3, and pink for target #4. Clearly, tracking dominant harmonics of each target provided a better classification and can be used in the track

association, as shown in figure 2. From figure 12, one notices that for the same track, occasionally target #1 is classified as something else. This can be easily corrected based on the positions of each target and their continued classification. Figure 13 shows how the QoI defined by (9) relates to the accuracy of tracking.

Measure of QoI for Classifier Output: Clearly, the dominant harmonic frequency of individual target is used for its classification—the natural choice for QoI of the classification would be its amplitude or its SNR. The QoI of the classifier is defined as

$$Q_c = S - t_h \tag{9}$$

where '*S*' denotes the SNR of the dominant harmonic frequency for the target in question, and t_h is the threshold.

4.3 Overall QoI

In the tracking approach illustrated in figure 2, three different key parts are identified—namely, location estimator, Kalman filter tracking, and target classifier. For each one of these key parts a QoI measure is defined in equation (3), (4) and (9). These QoI measurements are intended to provide an appropriate level of confidence to the observer as to how well each part is working. An effective overall QoI estimate for the entire tracking system would be highly valuable and would have to be generated using the individual QoIs.

A simple, conservative/pessimistic use of the three location qualities would adopt the minimum quality. However, since each is an approximation, we intuitively recognize that this will generally be pessimistic, and so actual opportunities (that would have been recognized from a god's-eye view) will be missed. For this reason, we explore a simple QoI re-estimator that emits a linear combination of the three. We seek to increase the effectiveness of the information source by producing a good QoI estimator for a specific decision-making scenario. Success will be indicated by a statistically significant benefit to using a QoI combinator over using the worst. Of course, we can design an experiment that favors a combinator. In fact, we do so, but note that the experiment is realistic.

As well as QoI attributes, themselves—falling generally under accuracy, timeliness, and trust types—we need QoI qualifiers to inform us as to how those attributes should be put to use. We are exploring the space of such qualifiers, but for our purposes here, we define two general, simple regimes. The first, in which the worst QoI is taken, is a pessimistic bound estimator, in which the qualifier is that we pass on the minimum or worst quality. The second is a weighted sum, in which each information source is assigned a weight. This weight is, in fact, a function of the data quality, and its shape is seen in our results. In further work we hope to derive this function from first principles. We define a straw-doll overall QoI function as a weighted sum of individual QoIs:

$$Q = w_t Q_t + w_k Q_k + w_c Q_c \tag{10}$$

Individual weights are to be either synthesized, based on the role each part plays in the overall quality of the system, or learned through experience. Some weights may have high value compared to others if the quality of the overall system is more dependent on those parts. We have a choice as to which attributes to aggregate, and which to leave separate.

In the introductory section we suggested a decision-making task of intercepting any tracked vehicle that is traveling northbound. This requires tracking the vehicle accurately and classifying it as the tracked vehicle. For example, if the classifier can classify the vehicle as a tracked vehicle with high confidence—that is, with high QoI value—the battlefield commander can order the tracked vehicle to be intercepted when it is approaching. The target tracker QoI along with the Kalman filter QoI show how well the target is being tracked, and the classifier identifies it as a tracked vehicle. Figure 14 shows the distance between the check post located at (160, 700) and tracked vehicle, individual QoIs, and the overall QoI. For overall QoI, we used the mean of all QoIs ($w_i = 1/3$) for all in (10). These weights can be appropriately learned with experience.

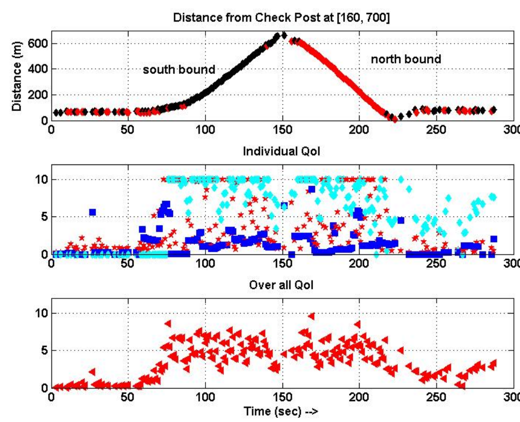

Figure 14: Distance from check post and QoIs

The decision to intercept the vehicle can be made during the northbound track, while the overall QoI is good—that is, above a threshold of 5.

5 Discussion and further work

Development of effective estimation and communication of information quality to decision-makers is an essential research target, when the range and number of sensing assets employed in sensing mission is rising rapidly. There are two ends of the spectrum: theoretical *ab initio* synthesis, and empirical discovery. Here we have begun to explore empirical approaches, with an eye to recognizing the theoretical issues as they become clear during testing. We have produced some basic, intuitive indicators of QoI calculated directly on the output of the sensing system and compared them with a view of ground truth known from the experiment that would not be available in normal operation. We find that these correlate well, particularly when combined in a simple but effective manner. This suggests

that some investment in analysis of existing test data against realistic decision making requirements is warranted, and that the use of simple combinators may be effective where extensive calculation in theater is not practical.

In the Kalman filter, we find in common with other researchers that the covariance matrix gives us a good handle on the accuracy of the filter's predictions, and, for our purposes, the quality of the information. The errors in DOA estimates are well-behaved, so we will filter the DOA estimates themselves, separately, or in combination with the derived Cartesian coordinates. The classifier success rate derives from processing excerpts from the same data as used in location estimation. The quality of data (QoD) will, therefore, impact both. This leads us to expect the observed correlation between tracking fidelity and classification success rates.

6 Conclusions

Effective construction and maintenance of situational awareness during tactical activity generally requires fusion of information sources. Estimates of the accuracy, confidence, and believability of information products are essential in the decision-making process. Bandwidth and electrical power constrained scenarios strongly motivate the minimization of computation and communications required. In this paper, tracking and classification accuracy of QoI attribute values are estimated, and candidate QoI qualifiers are defined for a tracking scenario. These are simple yes/no qualifiers that dictate which information should be fused, but to which simple policy gives an effective method with low computational complexity and the opportunity to report summarized QoI to a user in a quickly digestible form to simplify decision-making under high loading.

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